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Original scientific paper

ANALYSIS OF DGS BASED RECTANGULAR PATCH ANTENNA WITH ARTIFICIAL NEURAL NETWORK FOR WIRELESS COMMUNICATION

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Abstract. *This paper presents a defected Rectangular Microstrip Antenna (RMSA) with dimensions of 18x18x1.6 mm³, designed to operate at a center frequency of 7 GHz and within a range of 4.8 GHz to 10.37 GHz for wireless applications. The antenna's performance is evaluated using an Artificial Neural Network (ANN) model, which provides fast predictions of S_{11} values. The ANN model is trained on data from full-wave electromagnetic simulations. Five ANN algorithms—Adaptive Moment Optimizer, Scaled Conjugate Gradient, Bayesian Black-Box Optimization, Levenberg-Marquardt Algorithm, and Resilient Backpropagation—were used to assess the model's accuracy in predicting S_{11}. The results show that Resilient Backpropagation delivers the best prediction, closely matching both the electromagnetic simulations and experimental measurements, demonstrating strong agreement.*

Key words: *Artificial neural network, bandwidth, optimization, microstrip antenna*

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1. INTRODUCTION

Global communication is rapidly evolving, with wireless technologies playing an increasingly dominant role. This shift is largely due to the continuous advancements in wireless systems, where antennas are pivotal in enabling wireless connectivity across various devices and platforms by emitting electromagnetic waves in targeted directions. Among various antenna types, Microstrip Patch Antennas (MPAs) are particularly valued for their distinctive characteristics, making them a preferred choice in modern communication systems. MPAs are known for their lightweight design, cost-efficiency, compactness, ease of manufacturing, and adaptability to both flat and curved surfaces. These features make them suitable for a wide range of applications, including radar systems, medical devices, aerospace technology, RFID systems, and automotive communication. The design of MPAs can vary, with common shapes such as rectangular, circular, square, and triangular, each offering unique performance benefits [1]. Their low profile and minimal radiation loss further contribute to their widespread use in various technological fields. As the need for microstrip antennas grows, researchers have developed several methods to enhance their performance, focusing on bandwidth, gain, and radiation pattern improvements. These methods include incorporating slots on the patch, using defected ground structures, stacking, and applying metamaterials, all of which have significantly contributed to meeting the demands of modern communication systems. Traditional electromagnetic simulators like Ansoft HFSS, CST Microwave Studio, and FEKO have been essential tools for designing and analyzing antennas. These simulators use numerical methods such as the Finite Element Method (FEM), Finite Difference Time Domain (FDTD), Finite Difference Frequency Domain (FDFD), and Method of Moments (MoM) [2-4]. However, these tools, despite their effective exploration, have limitations, including lengthy simulation times for complex structures, high software costs, and also these tools are resource hungry, ie, they need machines with superior computing power [5].

In response to these challenges, machine learning, especially Artificial Neural Networks (ANNs), presents a promising alternative to conventional electromagnetic simulation tools. ANNs are particularly effective in solving complex, non-linear problems, making them ideal for optimizing microwave circuits and antennas. However, the success of an ANN model depends on factors like the training algorithm, the quality and size of the dataset, and the architecture of the network, including the number of layers and neurons. Incorporating machine learning into the antenna design process can greatly reduce simulation times and costs, while also improving the accuracy and reliability of designs. The application of ANNs to electromagnetic problems has the potential to transform the field, offering a more cost-effective and efficient solution compared to traditional methods [6].

Recently, Artificial Neural Networks (ANNs) have gained significant prominence in the design of patch antennas [7-9]. These networks are crucial for accurately determining key parameters such as input impedance and radiation characteristics in patch antennas [10-11]. An innovative approach utilizing neuro-fuzzy networks has been proposed for the rapid evaluation of resonant frequencies in patch antennas [12]. Additionally, ANNs have been implemented to predict the resonant frequency of circular patch antennas [13]. For antennas with thick substrates, tunnel-based ANNs are employed to identify resonant frequencies, with results validated against experimental and simulation data obtained from software like IE3D [14]. The reliability of ANN models in estimating the performance of microstrip antennas with thick substrates is demonstrated by the excellent agreement between predicted and experimental data. A novel method known as "Neurospectral" analysis has been introduced, combining neural techniques with spectral analysis in the wave number domain. Initially developed for the analysis of square patch antennas, this method can also be adapted for antenna synthesis [15]. A hybrid approach combining ANN and a fuzzy inference system (FIS) has been used in designing microstrip antennas (MSAs) of various shapes. In this method, the ANN is trained using the Bayesian regularization algorithm, while FIS parameters are determined through a combination of the least squares method followed by the backpropagation algorithm. The resonant frequency results obtained from this method for different MSA shapes demonstrate excellent alignment with experimental data [16]. For broadband performance optimization, a Genetic Algorithm (GA) has been used to tailor antenna designs. The GA utilizes input impedance predictions made by ANN across a wide frequency spectrum by varying antenna geometries, with the performance of the ANN being evaluated for accuracy and computational efficiency [17]. A slotted microstrip antenna with a substrate thickness of 1.588 mm has been proposed to achieve wideband characteristics using ANN techniques. Various training algorithms, including Multilayer Perceptron feed-forward backpropagation, ANN, and Radial Basis Function Neural Networks, have been applied for modeling, with the Radial Basis Function network demonstrating superior accuracy and speed compared to other backpropagation algorithms [18].

An ANN approach has also been proposed for the analysis of fractal antennas using Multilayer Perceptron Neural Networks (MLPNN), Radial Basis Function Neural Networks (RBFNN), and General Regression Neural Networks (GRNN), with the RBFNN identified as the most effective based on performance metrics [19]. An ANN model and Support Vector Machine (SVM) were used to analyze a Fabry-Perot resonator antenna, with all antenna parameters being analyzed using both models [20]. In another study, ANN techniques with Backpropagation Network (BPN) algorithms were applied to optimize a reconfigurable antenna with a hexagonal shape, operating in the 2.36-3.92 GHz frequency bands. The proposed structure reduced the complexity of the biasing circuit but lacked compactness and had low gain [21]. The optimization of Defected Ground Structure (DGS) parameters was presented using Feed-Forward Backpropagation Network (FFBPN) and ELMAN Backpropagation Network (EBPN) of ANN for a wearable hybrid fractal antenna operating in the S-band, C-band, and X-band, with FFBPN showing greater accuracy [22]. Using an ANN algorithm, a dual-band patch antenna with an H-slot DGS was designed for 5G applications, adopting a hybrid algorithm based on both feed-forward backpropagation and Levenberg-Marquardt (LM) learning to optimize the DGS dimensions for operation at 3.76 GHz (from 3.23 GHz to 4.27 GHz) and 6.1 GHz (from 5.6 GHz to 6.5 GHz) [23]. In another study, metamaterials based on Complementary Split-Ring Resonators (CSRRs) were designed for antenna miniaturization. The process involved utilizing Particle Swarm Optimization (PSO) to determine the dimensions of the planar CSRR structure, significantly reducing design time by integrating two machine learning (ML)-trained neural networks (NNs) [24]. A trained neural network efficiently mapped a planar multiband antenna's frequency to the ideal normalized geometry of the antenna patch. The chosen geometry was then duplicated, modeled in HFSS, and further fine-tuned using the Newton algorithm [25]. In [26], a patch antenna suitable for RF energy harvesting circuits at 2.4 GHz was proposed, with optimization performed more effectively using ANN compared to traditional simulation software.

Based on a survey of ANN-based patch antennas, which focuses on predicting parameters like resonant frequency, gain, and S11 using various algorithms, it is evident that adopting ANN significantly reduces analysis time and simplifies the prediction process. To streamline the process and avoid the complexity of traditional EM simulation, ANN is utilized to analyse a compact DGS-based rectangular patch antenna. Section 2 provides an introduction to the basic concepts of ANN. Section 3 presents the model of the RMS antenna, excited by a lumped port. Section 4 details how the datasets are obtained through simulation and subsequently used in the training and testing processes. In Section 5, five ANN algorithms are employed to analyse the antenna's performance in terms of S_{11}. Finally, Section 6 offers conclusions and suggests possible topics for future research.

2. BRIEF CONCEPT OF ANN

An Artificial Neural Network (ANN) consists of interconnected neurons arranged into layers, and information is processed by modifying weights and biases in the connections between these neurons, as illustrated in Figure 1. Within this structure, signals labelled as xi and xn emanate from signal sources or other neurons [27-28] Here, wi represents the weight for the ith connection, and θ acts as the threshold, commonly referred to as bias. The inputs and outputs have some relationship which can be illustrated as follows:

$$y = f\left(\sum (w_i \cdot x_i) - \theta\right) \tag{1}$$

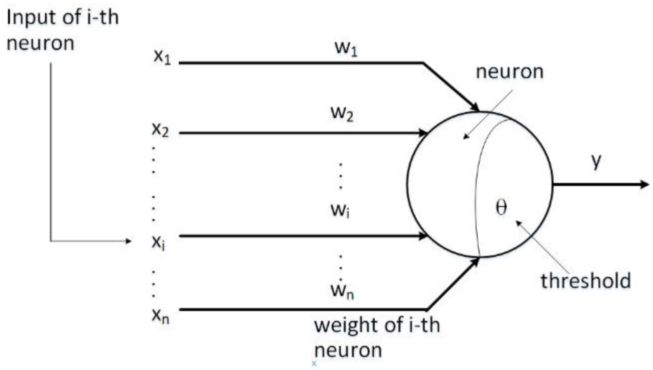


Fig.1 ANN basic model

The ANN training process involves providing the network with input data and corresponding target data (desired output data), collectively referred to as learning data. Prior to training, the network is given this information to learn and the network arrange the weights of each unit to reduce the error among desired and actual output. This error is quantified as the mean square error (MSE) [29]. The MSE signifies the growing error among the network's output and the target output, serving as the performance index [30]. Mathematically, the MSE is expressed as:

$$\text{Mean squared error (MSE)} = \frac{1}{n}\sum_{i=1}^{n=i}\left(\sum_{i=1}^{n}(ANN(x_i) - y_i)^2\right) \tag{2}$$

Where n indicates the number of samples and yi is desired output, ANN(xi) signifies the ANN output, and the summation is performed over all samples in the dataset.

The accuracy in an Artificial Neural Network (ANN) refers to the percentage of correct predictions made by the model on a given dataset. It is a metric used to evaluate how well the model performs in terms of correctly classifying or predicting outcomes.

$$\text{Accuracy (\%)} = \frac{|\,\text{ANN}(x_i) - |\,\text{ANN}((\text{x}_i) - y_i)\,||}{\text{ANN}(x_i)} \cdot 100 \tag{3}$$

3. Design Specifications of Proposed Antenna

3.1. Design of Proposed Antenna

Initially a rectangular patch antenna with dimensions L1 as length and W1 as its width is placed at height ‘h’ on FR4 substrate with ground plane of dimension $18x18mm^2$. The design equations are illustrated in equations 4-7.

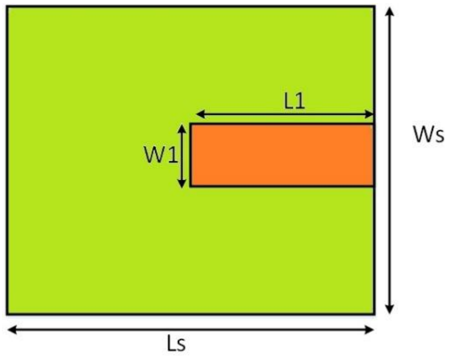
$$W = \frac{c}{2 f_0 \sqrt{\frac{\varepsilon_r + 1}{2}}} \tag{4}$$

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2} \left(\frac{1}{\sqrt{1 + \frac{10h}{W}}} \right) \tag{5}$$

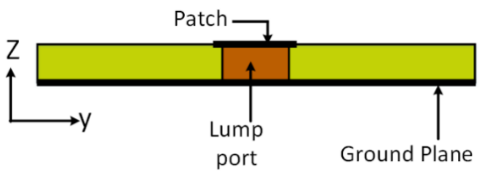
$$\Delta l = 0.412h \frac{(\varepsilon_{eff} + 0.3)\left(\frac{W}{h} + 0.264\right)}{(\varepsilon_{eff} - 0.258)\left(\frac{W}{h} + 0.813\right)} \tag{6}$$

$$l_{eff} = \frac{c}{2 f_0 \varepsilon_{eff}} \tag{7}$$

In the ground plane of the RMSA antenna, rectangular slots are embedded which results in defected ground as shown in Figure 2(c). Figure 2 (a), (b) and (c) depict top, side and bottom view respectively of the proposed antenna which is a rectangular patch constructed on an FR4 substrate having defected ground. The table 1 is illustrating its dimensions in mm.



(a)



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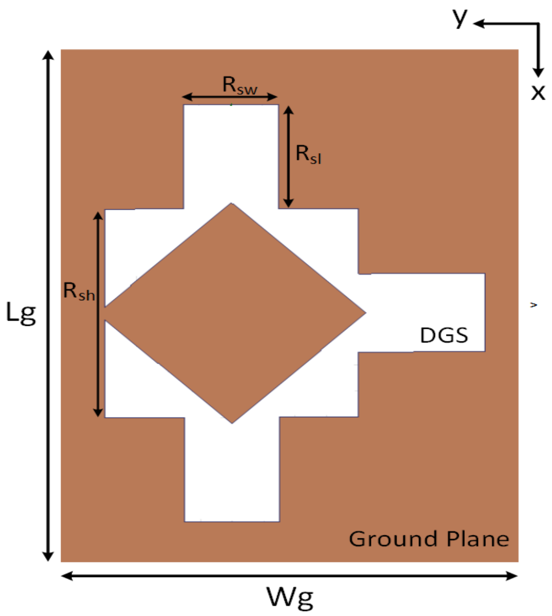


(c)

Fig. 2 (a) Top view (b) bottom view (c) side view: Antenna structure

Table 1 Dimensions in mm of suggested Antenna

Parameter	Value
Ls as substrate length	18.0
Ws as substrate width	18.0
H as substrate height	1.6
L1 as patch length	9.0
W1 as patch width	7.0
Lg as ground plane length	18.0
Wg as ground plane width	18.0
Rsl as slot length	3.0
Rsw as slot width	5.0
Slot height in the ground plane, Rsh	8.0

The incorporation of the DGS structure alters the effective inductance and capacitance, leading to changes in the surface current distribution and input impedance. By optimizing impedance matching, the antenna reduces the amount of power reflected back to the source, leading to improved return loss performance. Moreover, by optimizing impedance matching, the antenna reduces the amount of power reflected back to the source, leading to improved return loss performance, eventually enhancing the gain by improving radiation efficiency and suppressing the surface waves. Figure 3 shows that on incorporating slots in ground plane, the resonant frequency shifts to lower side of frequency. Figure 4 (a) and (b) depict the current distribution on top and bottom surface of the proposed antenna respectively. It has been observed that slots in the ground plane disrupt the surface current, causing a high current density to concentrate along the edges of the slots and at the boundary of the central region of the ground plane.

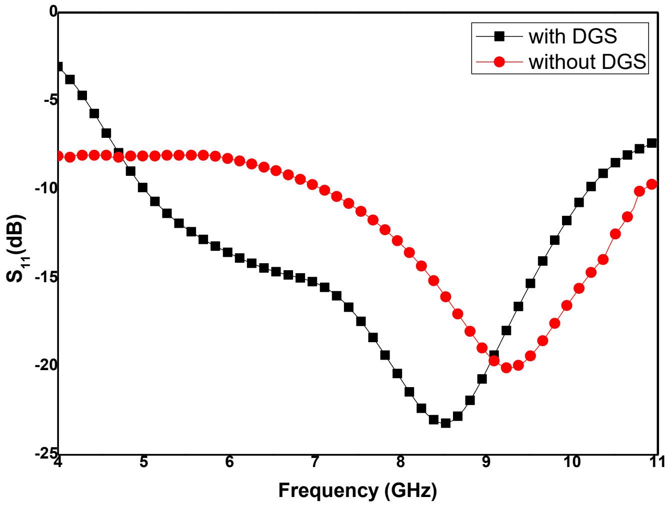
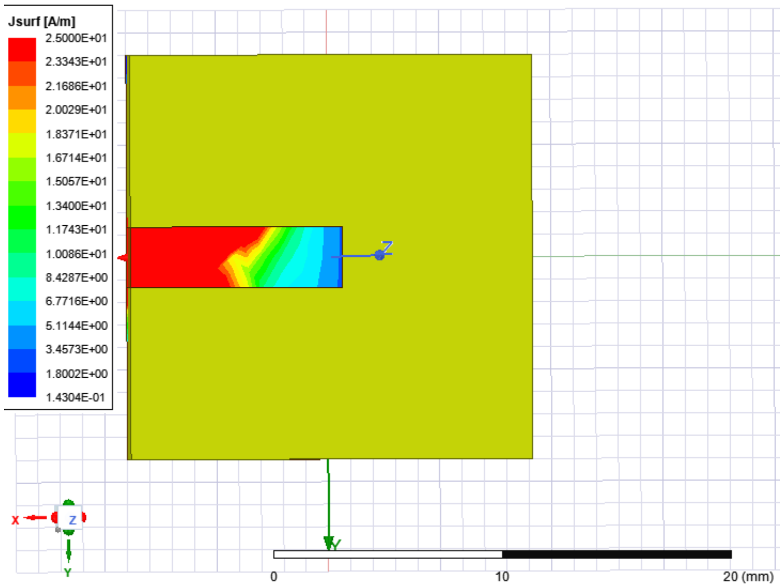
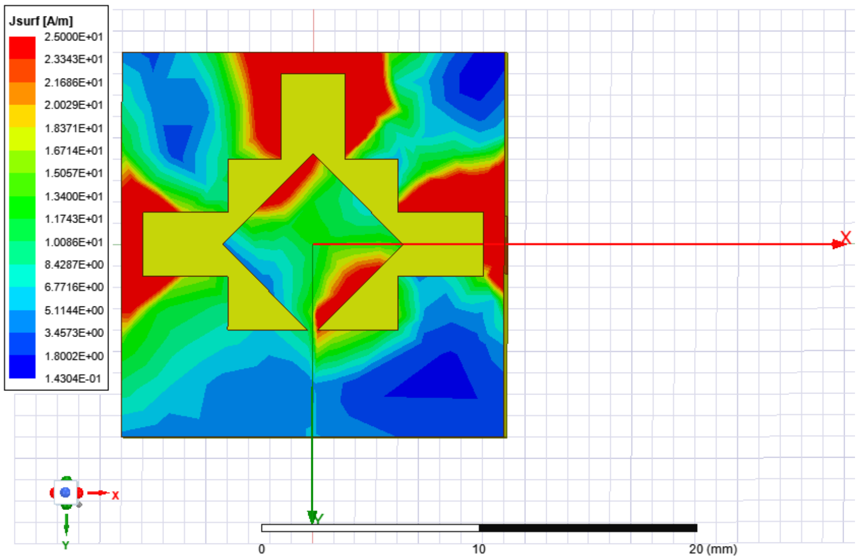


Fig. 3 S_{11} variation with frequency (with and without DGS)



(a)



(b)

Fig. 4 Current density (a) Top view (b) bottom view

4. ANN Model and Various Algorithms Adopted for Analysis of Proposed Antenna

To generate a dataset, the proposed antenna design is implemented using the HFSS EM simulator. This dataset will serve as the basis for making predictions. After the simulations conducted on HFSS, the resulting data is gathered and stored. The dataset, obtained from the antenna simulations, comprises 1300 records and is structured variables five and one as independent and dependent variables respectively. The dataset is collected by varying the length of patch, width of patch, slot length, width of slot, frequency and thickness of substrate. Figure 5 depicts the ANN model comprising 6 inputs having output and hidden layer as one with 80% data consumed for training,10% data for validation and testing each. The proposed ANN model can be used to predict the S11 for new antennas as long as they belong to the same design space or family.

4.1. Data set generation

For data set generation purpose, Patch length of rectangular patch was varied from 9.4 to 9.5 mm keeping a step size of 0.1 mm, which provides two different values of this parameter. Similarly, patch width of rectangular patch was varied from 2.6 to 2.8 mm with a step size of 0.1 mm, which provides us three different values. Slot length varied from 4 to 6 mm with a difference of 1mm, which provides us three different values. Slot width varied from 2 to 4 mm with a difference of 1 mm, which provides us three different values. Substrate height varied from 1.5 to 1.6 mm with a difference of 0.1 mm, which provides two different values and frequency varied from 4 to 11 GHz with a difference of 0.07 GHz, which provides 1300 different values.

4.2. Training models

Figure 5 shows the ANN model designed for our proposed antenna. The model is trained using the dataset derived from the HFSS. The ANN architecture includes one hidden layer with 64 neurons, utilizing the ReLU activation function, and an output layer with a single neuron for regression tasks. In this paper five algorithms are used namely Adaptive Moment Optimizer (Adam), Scaled Conjugate Gradient (SCG), Bayesian Black-Box Optimization (BBO), Levenberg-Marquardt (LM) algorithm and Resilient Backpropagation (Rprop). The Adam optimizer, with a learning rate of 0.001, SCD Optimizer with Nesterov Momentum (0.01 Learning Rate) is employed to optimize the model. The learning rate in BBO, LM and Rprop.is optimized within a range from 0.0001 to 0.01 with the specific value selected based on the model's performance during the tuning process. This design aims to achieve a balance between complexity and efficiency, enabling the network to capture non-linear patterns in the data while reducing the potential for overfitting. The optimal model is determined based on accuracy and lowest Mean Squared Error (MSE) value. During training, features and target values are standardized to maintain consistent scaling, improving the model's stability and performance. The data set thus prepared is divided into 80% for training, 10% for validation, and 10% for testing to facilitate effective training and unbiased evaluation. For evaluating the Model performance, Mean Squared Error (MSE), with percentage accuracy offering further insights into prediction quality is estimated. To prevent overfitting, the model's performance is closely monitored through the validation set, and although regularization techniques are not applied in this version, they could be considered to further address overfitting if necessary.

(a) Adaptive Moment Optimizer Algorithm:

Adam, short for Adaptive Moment Optimizer, represents a very effective and often used optimizer for training ANN models. Specifically crafted for minimizing unconstrained, smooth functions, Adam proves well-suited for training neural networks. Acknowledged for its speed, the performance of Adam may be influenced by the unique architecture of the neural network and the random initialization of neuron weights [24].

(b) Scaled Conjugate Gradient Algorithm:

SCG, or Scaled Conjugate Gradient, serves as an optimization algorithm extensively applied in ANN training. By integrating the conjugate gradient method with a scaled approach, SCG excels in efficiently optimizing both time and accuracy. This makes it a highly favoured choice for training neural networks [23].

(c) Bayesian Black-Box Optimization:

This is a method designed for optimizing functions that are difficult or costly to assess directly. It employs probabilistic models, like Gaussian Processes, to forecast function values and gauge uncertainty. By utilizing an acquisition function, this technique strategically chooses where to evaluate next, aiming to balance exploration with exploitation. This strategy reduces the total number of function evaluations required to identify the optimal solution. It's often applied in areas such as tuning hyperparameters and handling other expensive function evaluations.

(d) Levenberg-Marquardt algorithm:

The Levenberg-Marquardt (LM) algorithm is an iterative method designed for optimizing non-linear least squares problems. It merges elements of gradient descent and the Gauss-Newton approach to effectively locate local minima. The algorithm adjusts its step size dynamically, allowing it to leverage the rapid convergence of the Gauss-Newton method while maintaining the stability of gradient descent. This versatility makes it well-suited for tackling complex or ill-conditioned functions. The LM algorithm is commonly applied in machine learning and data fitting to fine-tune model parameters.

(e) Resilient Backpropagation:

The Resilient Backpropagation (Rprop) optimizer is designed to enhance the training process of neural networks by focusing on the direction of gradients rather than their magnitude. This approach helps manage varying gradient scales, improving stability. Rprop adjusts the learning rate for each weight individually, which speeds up convergence and mitigates issues like vanishing or exploding gradients. It is especially useful in environments with noisy gradients or complex loss functions. Although not as prevalent in current libraries, Rprop's principles are akin to those of other optimizers like RMSprop available in TensorFlow/Kera

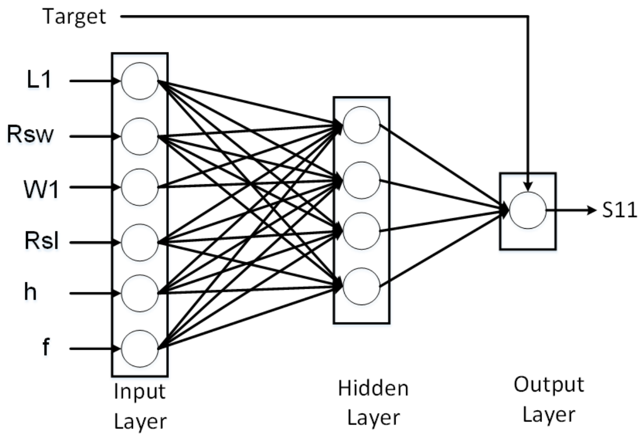
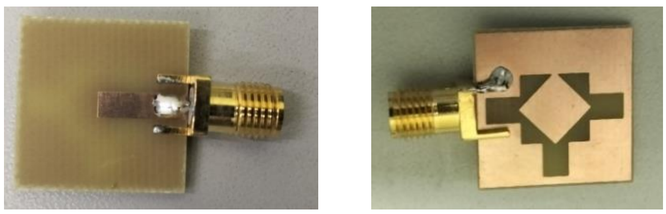


Fig. 5 ANN model

5. RESULTS

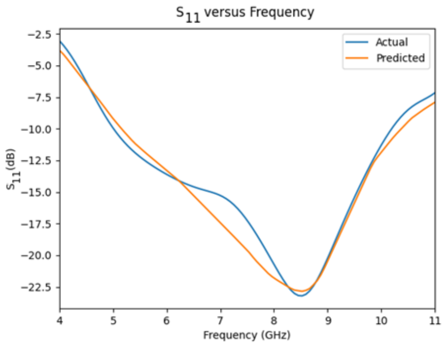
Figure 6 illustrates the prototype model of the proposed antenna, displaying its physical design and construction. The performance of this antenna was assessed using a Network Analyzer. The S_{11} parameter plots shown in Figures 7(a), (b), (c), (d) and (e) were generated after applying and testing five distinct training algorithms with an Artificial Neural Network (ANN). These algorithms include Adam, Scaled Conjugate Gradient (SCG), Bayesian Black-Box Optimization (BBO), Levenberg-Marquardt (LM), and Resilient Backpropagation (Rprop). The figures highlight the return loss characteristics of the antenna and how they vary depending on the chosen algorithm. Table 2 provides a summary of the Mean Squared Error (MSE) values for each algorithm. This table offers a comparative analysis of the error rates associated with the different training methods.

The BBO algorithm emerges as the most effective, achieving a prediction accuracy exceeding 95.8 %. It also features a remarkable convergence time of only 2 milliseconds. This performance underscores BBO's efficiency and accuracy, making it an excellent choice for optimizing ANN training across various network configurations.



(a) (b)

Fig. 6 (a) Top view (b) Bottom view: Fabricated model



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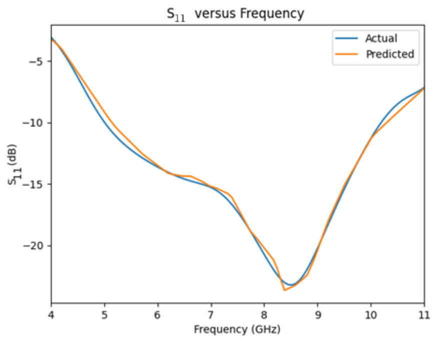

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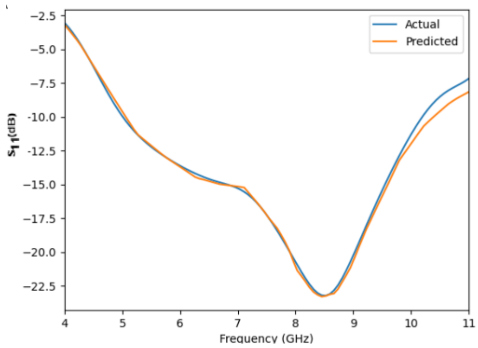

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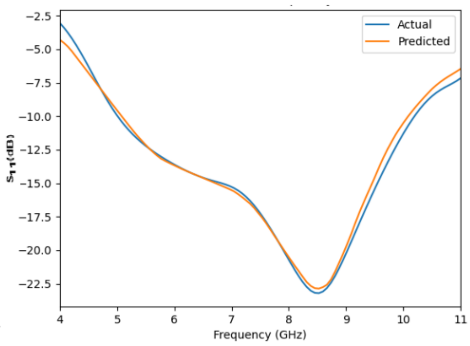

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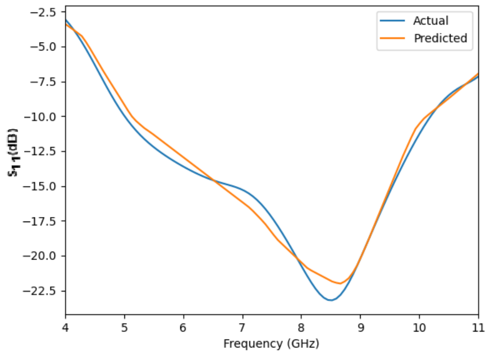


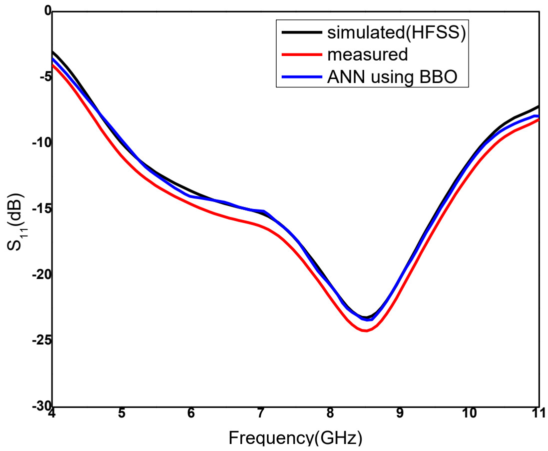
(e)

Fig. 7 S_{11} plot of proposed antenna by using (a) Adam (b) SCG (c) BBO (d) LM (e) R_{prop}

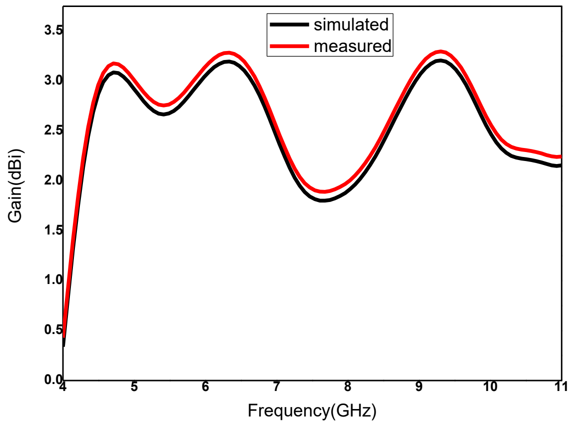
Table 2 Performance metrics of ANN

S No	Algorithm	MSE	% Accuracy
1	Adam	0.14	88
2	Scaled Conjugate Gradient	0.08	92
3	Bayesian Black-Box Optimization	0.05	95.8
4	Levenberg-Marquardt algorithm	0.087	92.7
5	Resilient Backpropagation	0.03	88.8

Figure 8 displays a detailed S_{11} plot, showcasing the performance of the proposed antenna across various datasets. The plot includes simulation data within a frequency range of 5 GHz to 10.2 GHz, offering theoretical predictions of the antenna's behaviour. This is complemented by experimental measurements, which span from 4.8 GHz to 10.37 GHz, and closely match the simulation results. This alignment suggests that the theoretical models provide an accurate representation of the antenna's real-world performance.



(a)



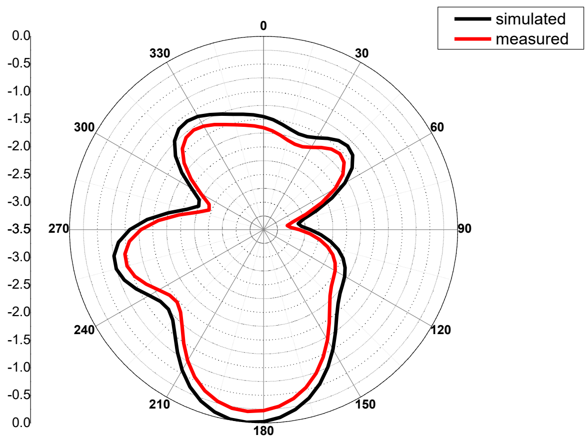
(b)

Fig. 8 Proposed antenna variation of (a) S_{11} plot (b) Gain plot

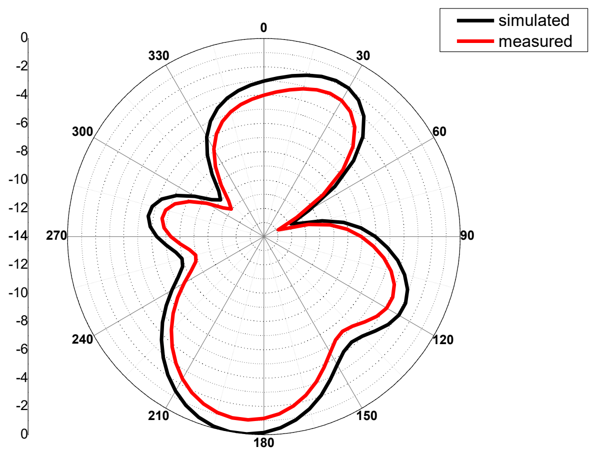
The plot also features S_{11} values predicted by Artificial Neural Network (ANN) algorithms. S_{11}, is an important metric in antenna design that measures the proportion of power reflected back from the antenna compared to the power that is transmitted. The close agreement between simulated, measured, and ANN-predicted S_{11} values highlights the accuracy of the ANN predictions and the efficacy of the antenna design.

Further, the proposed antenna is anticipated to achieve a peak gain of 3.4 dBi. This gain measurement reflects the antenna's capacity to focus energy efficiently within the specified frequency range, suggesting its potential for effective use in various applications. The high predicted gain underscores the antenna's well-engineered design and its suitability for practical deployment.

Figure 9 shows that at xz and xy plane, proposed antenna with centre frequency of 7 GHz has stable radiation characteristics. The radiation pattern shown in figure 7, demonstrates a non-omnidirectional characteristic, marked by clear lobes and nulls. This indicates that the antenna radiates more intensely in certain directions, creating petal-shaped lobes. The simulated and measured patterns are largely consistent, confirming the antenna’s intended performance, with slight differences possibly due to real-world factors like manufacturing variations or environmental influences. Such radiation behaviour is common in antennas with slots or asymmetric structures, where the radiation is enhanced or diminished in specific directions due to wave interference effects



(a)



(b)

Fig. 9 Radiation pattern: (a) xz plane (b) xy plane

The table 3 shows the proposed antenna is compact and with improved bandwidth in comparison to other ANN based antenna. From table 3, it is clear and evident that the proposed antenna is more compact than the work cited in the table.

Table 3 Comparison table of our proposed antenna with other cited ANN based Antenna

Ref. No.	Antenna Type	Dimension in mm^3	Number of Frequency Bands	Impedance Bandwidth in GHz (%)	ML model Employed	Error
[16]	Rectangular MSA	50x50x1.6	1	1.5-3.0 (66.6%)	ANN+ANFIS	Absolute error 322 MHz
[18]	Slotted MSA	15.5x18.48x1.58	1	9.75-10.5 (4.9%)	ANN with RBF	MSE 7.2334 e-029
[20]	Fabry Perot Resonator Antenna	72 × 72x1.6	1	8-12.0 (40%)	ANN	Average MAPE 0.605%
[21]	Hexagonal slotted MSA	50 x 50x 1.6	1	2.36-3.92 (71.4%)	ANN with BPN algorithm	-MSE 9.0e 6.
[22]	Wearable hybrid fractal antenna	59x51x1	3	2.5,4.9,&7.6 <10%	ANN using FFBPN	Average Absolute error 0.01881
[23]	H slotted DGS patch antenna	34x20x1	2	3.23-4.27 5.6-6.5	ANN using LM	MSE in two bands 0.143 and 0.201
[25]	Multi-Band Planar Antennas	34.1 x 34.1 x1.0	3	2.4,3.6 & 4.9 <10%	ANN using newton algorithm ANN with FBPN & LM	MSE for FBPN 2.03e20 MSE for LM 0.27
[26]	MSA	40x40x1.5	1	2.4GHz	ANN	RME 4%
Proposed Work	Rectangular Microstrip Antenna	18x18x1.6	1	4.8-10.37 (73.4%)	ANN using BBO	0.05

6. Conclusion

The paper explores well the designing and optimization of a compact lumped-fed rectangular patch antenna. The design was finalized after exploring all the features, the model was then fabricated and tested. The model operated in a frequency range from 4.8 GHz to 10.37 GHz. The antenna maintained stable radiation characteristics throughout its operational band, making it well-suited for various wireless communication applications. Five Artificial Neural Network (ANN) namely Adaptive Moment Optimizer, Scaled Conjugate Gradient, Bayesian Black-Box Optimization, Levenberg-Marquardt algorithm and Resilient

Backpropagation, were utilized to forecast optimal S_{11} values for the antenna design parameters. The findings reveal that these ANN approaches deliver substantial advantages over traditional electromagnetic (EM) simulators in terms of both efficiency and accuracy. It is also concluded that the Bayesian Black-Box Optimization provides the highest accuracy in comparison to rest of the algorithms. The application of ANN methods facilitated a more streamlined design process and enabled precise antenna performance predictions with reduced computational effort.

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